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BEARING DIAGNOSTICS BASED ON PATTERN RECOGNITION OF STATISTICAL PARAMETERS

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ABSTRACT

In this paper a new method is proposed to diagnose bearing defects based on pattern recognition of statistical parameters. This pattern recognition problem can be described as transformation from the pattern space to the feature space and then to the classification space. Based on trend analysis of six commonly used statistical parameters, four parameters, namely, RMS, Kurtosis, CrestFactor and ImpulseFactor are selected to form a pattern space. A 2-D feature space is formulated by a nonlinear transformation. An intraclass transformation is used to cluster the data of different bearing defects into different regions. The classification space is constructed by a piecewise linear discriminant function. The proposed method is tested by first training the classification space using the data of the bearings with seeded defects and then utilizing the classification space to diagnose the defected bearings. The results show that it is an effective method for bearing diagnostics.

1. Introduction

The subject of roller bearing diagnostics has been studied over the last twenty five years because they are used in all rotating machinery from small, medium to large size (Rao, 1996). Common failure of roller bearings includes spalling, corrosion, brinelling, etc. These defects induce repetitive vibrations when bearing elements encounter them (McFadden and Smith, 1984a,b). The objective of bearing diagnostics is to identify the type of defects by means of the technologies involving measuring and processing of these defect-induced vibration signals.

In practice, spectrum analysis is the most common method, used together with trend analysis, for bearing diagnostics. This method detects the frequencies of the repetitive impulses generated by the bearing defects. The method is effective for detecting single defects which exhibit distinct defect frequencies. However, it becomes less effective when defect frequencies are not distinct, such as multiple defects. Time domain analysis may overcome the weakness of spectrum analysis, as statistical parameters can provide information such as the shape of the amplitude probability distribution and the energy level of the vibration signals. Much of research work (Braun, 1986, Howard, 1994, and Rao, 1996) has been done in using these parameters individually to detect the bearing defects, and the results have shown that each parameter is only effective for certain defects. For example, spikiness of the vibration signals indicated by CrestFactor and Kurtosis implies incipient defects, while the high energy level given by the value of RMS and Peak indicates severe defects.

An intuitive idea is to combine these statistical parameters into a weighted index to take different defects into consideration. Based on this idea, we propose in this paper a bearing diagnostic method based on pattern recognition of statistical parameters. This pattern recognition problem can be described as transformation from the *pattern space* to the *feature space* and then to the *classification space.* Based on trend analysis of six commonly used statistical parameters, four parameters, namely, *RMS, Kurtosis, CrestFactor* and *ImpulseFactor* are selected to form a pattern space. A feature space is formulated by a nonlinear transformation and its dimension is defined as two, for the purpose of displaying results on a 2-dimensional plane. An intraclass transformation is used to cluster the data of different bearing defects into different regions. Classification of bearing defects is done by the discriminant function which is generated through a supervised learning process. The discriminant function relates different bearing defects to different regions in the classification space. The proposed method is tested by first training the classification space using the data of the bearings with seeded defects and then utilizing the classification space to diagnose the defected bearings.

2. Pattern Recognition of Statistical Parameters

The idea of pattern recognition of statistical parameters is first to construct the pattern space based on statistics analysis and then perform pattern recognition analysis using statistical parameters. In this section, we describe how to select the statistical parameters to form the pattern space for bearing diagnostics. In the following two sections, we will describe how to form the feature space and classification space.

2.1 Selection of Pattern Space

Six commonly used statistical parameters for bearing diagnosis (Howard, 1994) are Peak, RMS, CrestFactor, Kurtosis, ImpulseFactor, and ShapeFactor, which are considered here to form the pattern space. In terms of the sampling data vector denoted by $\mathbf{s} = [s_1,..s_n]$, these parameters can be defined as follows:

$$Peak = \frac{1}{2}(\max(s_i) - \min(s_i)) \tag{1}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})^2} \tag{2}$$

$$CrestFactor = \frac{Peak}{RMS} \tag{3}$$

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})^4}{RMS^4} \tag{4}$$

$$ImpulseFactor = \frac{Peak}{(1/N)\sum_{i=1}^{N}|s_i|} \tag{5}$$

and

$$ShapeFactor = \frac{RMS}{(1/N)\sum_{i=1}^{N}|s_i|} \tag{6}$$

where $\bar{s}$ denotes the mean value of the time domain signal.

Note that Peak and RMS have a unit, while the other four parameters are dimensionless. For normalization, we use the RMS value of the undamaged bearing data, denoted by RMS_0, as a normalizing parameter. Based on our experiment, we have found that RMS_0 can improve the robustness of the energy level parameters, namely, Peak and RMS, against variation in the bearing operating conditions. RMS_0 is determined by considering all the possible loads and rotating speeds for the bearing under study. In terms of RMS_0 we can rewrite eqns. (1) to (6) and define the following normalized vector **z**

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \\ z_6 \end{bmatrix} = \begin{bmatrix} Peak / RMS_o \\ RMS / RMS_o \\ CrestFactor \\ Kurtosis \\ ImpulseFactor \\ ShapeFactor \end{bmatrix} \tag{7}$$

It has been shown in the literature (Howard, 1994) that Peak and RMS values directly reflect the energy level of the vibration signals. Since the localized bearing defects result in structural vibrations, these two parameters are generally used to indicate the presence and severity of the bearing defects. CrestFactor and Kurtosis are seen less dependent on the vibration level, but sensitive to the spikiness of the vibration signals. As such they can provide early indication of significant changes in the vibration signals. As the damage increases, the vibration signals become more random, and the values of CrestFactor and Kurtosis could decrease to the undamaged level. ImpulseFactor and ShapeFactors have similar effects like CrestFactor and Kurtosis.

2.2 Trend Analysis

Since the statistical parameters of bearing vibration signals are affected by the bearing operating conditions, *e.g.* the rotating speed and load, trend analysis is conducted to investigate the effect of the bearing operating conditions on the statistical parameters. We intend to use two energy level parameters z_1 and z_2, while to examine the similarity among the other four parameters z_3 to z_6, which pertain to spikiness.

Table 1 summarizes the trend analysis. With respect to the speed, Crest factor and Kurtosis have a similar trend, whereas ImpulseFactor and ShapeFactors share another similar trend. With respect to the load, the four parameters show a similar trend.

Table 1 Summary of the trend analysis

Variable	Speed	Load
z_3	+	*
z_4	+	*
z_5	#	*
z_6	#	*

+, # and * indicate the similarity

Based on the trend analysis, we choose Kurtosis against CrestFactor, and ImpulseFactor against ShapeFactor. Note that Peak/RMS_o (z_1) is similar to CrestFactor, and based on our numerical experiment, we use the latter instead of the former. Hence, we define the following vector $\mathbf{x}_p$ to form the pattern space

$$\mathbf{x}_p = \begin{bmatrix} x_{p1} \\ x_{p2} \\ x_{p3} \\ x_{p4} \end{bmatrix} = \begin{bmatrix} RMS / RMS_o \\ Kurtosis \\ CrestFactor \\ ImpulseFactor \end{bmatrix} \tag{8}$$

The dimension of our pattern space is four.

3. Selection of Feature Space

3.1 Feature Extraction

Probably, the most important aspect of pattern recognition is selection of feature space. Proper and efficient feature extraction allows large dimension reduction yet retaining as much as possible the useful information. Constructing a feature space by a planar image is especially advantageous owing to the fact that a planar image of data can be readily perceived and analyzed by a human observer. For bearing diagnostics, we start by recording the vibration signals using acoustic sensors or accelerometers. The raw data are a series of numbers representing the amplitude of signals at discrete times. Although by using the aforementioned statistical parameters and trend analysis, dimension is reduced to four, it is desirable that two indices should be extracted which gives a combination of the other parameters.

We consider two key information that statistical parameters might give us about the bearing vibration signals. One is the spikiness, and the other includes the shape of the amplitude distribution density and the energy level of the vibration. The first one is straightforward and can be provided by CrestFactor, or Kurtosis, or Impulse Factor. We choose Kurtosis in view of its robustness in variation with the operating conditions. Based on the studies reported in the literature (Howard, 1994), the shape of the amplitude density distribution can be reflected by the statistical parameters pertinent to the impulsiveness of the signal, that is, Crest Factor, Kurtosis and the Impulse Factors. Therefore, the second feature is selected as

$$\frac{RMS}{RMS_0} \cdot \frac{CrestFactor}{Kurtosis} + ImpulseFactor \tag{9}$$

By substituting eqn. (3) for CrestFactor into eqn. (9) and using a logrithmatic scale for the second feature, the vector defining the feature space is given as

$$\mathbf{x}_f = \begin{bmatrix} x_{1f} \\ x_{2f} \end{bmatrix} = \begin{bmatrix} Kurtosis \\ \log\left(\dfrac{Peak}{RMS_o \cdot Kurtosis} + ImpulseFactor\right) \end{bmatrix} \tag{10}$$

The dimension of our feature space is two. Accordingly, the prototype vector representing a sample for k class of bearing defect is defined as

$$\mathbf{y}_{fm}^{(k)} = \begin{bmatrix} y_{f1m}^{(k)} \\ y_{f2m}^{(k)} \end{bmatrix} \tag{11}$$

Note that the actual statistical parameters used in the computation of our approach are Peak, RMS_o, Kurtosis and ImpulseFactor.

Figure 1 shows the feature space constructed using eqn. (10) considering a range of operating speed and load conditions as well as with incipient and later-stage defects. It can be seen that samples representing different groups are scattered and overlapped. This will impose difficulties in classification. For this reason, the intraclass transformation is applied to introduce the clustering effects on the samples within the same class.

3.2 Intraclass Transformation

The intraclass transformation is designed to increase the clustering of prototypes in the same class. This is realized through minimization of a metric between the points defining the class. For the kth class, there are a total of M_k prototypes $\mathbf{y}_m^{(k)}$ (m = 1,...M_k), each being a point in the 2-dimensional feature space. The intraclass transform in the feature space is defined as:

$$\mathbf{y}'^{(k)}_{fm} = \mathbf{W}^{(k)}\mathbf{y}_{fm}^{(k)} \tag{12}$$

where by denoting σ_1^2 and σ_2^2 the variances of the two variables in the feature space, $\mathbf{W}^{(k)}$ is a diagonal matrix given as

$$\mathbf{W}^{(k)} = \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}\right)^{-1} \begin{bmatrix} \dfrac{1}{\sigma_1^2} & 0 \\ 0 & \dfrac{1}{\sigma_2^2} \end{bmatrix} \tag{13}$$

Variances σ_1^2 and σ_2^2 are determined respectively by the first and second row of the following data matrix $\mathbf{Y}^{(k)}$ formed by M_k prototypes

$$\mathbf{Y}^{(k)} = \begin{bmatrix} y_{f11}^{(k)}, & \cdots & y_{f1M_k}^{(k)} \\ y_{f21}^{(k)}, & \cdots & y_{f2M_k}^{(k)} \end{bmatrix} \tag{14}$$

Through the intraclass transformation, the mean square intraset distance of the kth class is minimized (Andrews, 1972). It can be seen from eqn. (13) that the two coordinate dimensions are inversely proportional to the variance of their own dimension. This can be interpreted as stating that a small weight is to be given to those coordinates with large variances because these particular coordinates have little in common over the prototypes of the *k*th class. For those dimensions with near constant values the variance will be small which will imply large weighting.

Figure 2 shows the effects of the intraclass transformation on the same set of data used to obtain Figure 1. Clearly, the samples belonging to the same class are clustered

4. Formation of Classification Space

Recall that the problem of forming the classification space is to partition the feature space. For given *K* classes, $S_1,\ldots,S_k,\ldots,S_K$, mathematically, this problem is to find a function that can measure each point in the feature space in terms of its degree of membership to a given class. This function is called the discriminant function in pattern recognition and is defined such that for all points x_f in the feature space within the region describing S_k, there exists a function $g_k(\mathbf{x})$ such that

$$g_k(\mathbf{x}_f) > g_j(\mathbf{x}_f) \quad \forall \mathbf{x}_f \in S_k \ \ and \ \forall k \neq j \tag{15}$$

In other words, within the region S_k the *k*th discriminant function will have the largest value.

The piecewise linear discriminant function is used which can approximate the nonlinear boundaries separating the different class regions. This function is defined by the minimum distance between a point $\mathbf{x}_f$ and the prototype points in class S_k

$$d(\mathbf{x}_f, S_k) = \min_{m=1,\ldots,M_k} \{d(\mathbf{x}_f, \mathbf{y}_{fm}^{(k)})\} \tag{16}$$

Point $\mathbf{x}_f$ belongs to class S_k if the distance is minimum. The classification then becomes to determine the smallest distance between all of the prototypes of S_k and the unknown $\mathbf{x}_f$. Mathematically, this can be written as

$$\mathbf{x}_f \in S_k \ \ if \ \ d(\mathbf{x}_f, S_k) = \min_k d(\mathbf{x}_f, S_k) \tag{17}$$

Through mathematical manipulation (Andrews, 1972), the piecewise linear discriminant function can be given as

$$g_k(\mathbf{x}_f) = \max_{m=1,\ldots,M_k} \{\mathbf{x}_f^T \mathbf{y}_{fm}^{(k)} - \frac{1}{2} \mathbf{y}_{fm}^{(k)^{\mathrm{T}}} \mathbf{y}_{fm}^{(k)}\} \tag{18}$$

The boundaries separating the different class regions are determined by the following equation

$$g_k(\mathbf{x}_f) - g_j(\mathbf{x}_f) = 0 \tag{19}$$

Figure 3 shows the boundaries determined by eqn. (19), providing a very distinct partition of the different class regions for the different bearing defects.

5. Case Study

5.1 Experiment Set-Up

The developed method was used to diagnose the defects of the tapered roller bearings used in railway freight cars. Since the damaged bearings could cause train derailment, railway bearing diagnostics is very important. A bearing test rig was set up in the Transportation Technology Center of the Association of American Railroads. Two types railway bearings, F and E, were tested with seeded defects under two different loads, 8K lbs and 33K lbs for the first type and 8K and 27.5K lbs for the second type. The wheel travel speed tested was from 25 mph to 80 mph. The data used was the vibration signals measured from the bearing housing and sampled at 523kHz. Table 2 summarizes the bearing condition classes considered in our study.

Table 2 Bearing condition classes

Class	Symbol	Condition
C_1	1	undamaged
C_2	2	single spall on outer race
C_3	3	multiple spall on outer race
C_4	4	single spall on inner race
C_5	5	multiple spall on inner race
C_6	6	broken roller

5.2 Bearing Diagnostics

Bearing diagnostics was carried by using our program written in MATLAB. In computation, first, the statistical parameters were calculated using eqns. (1)-(6). Each sample was then located in the feature space according to eqn. (10), as shown in Figure 1. Through the intraclass transformation (eqn. (12)), the prototypes were clustered in the feature space, as shown in Figure 2. We then constructed the six piecewise linear discriminant functions by eqn. (19), and determined the classification space through learning from the prototype data of the six classes, as shown in Figure 3. To test the effectiveness of this method, we used a set of data with an unknown type of defect. We used our program and located the testing data in the region of broken rollers, as shown in Figure 4 in "+" symbol. The result was verified by checking that bearing which indeed had a broken roller defect.

6. Conclusions

A bearing diagnostics method is developed based on pattern recognition of statistical parameters. This method is unique in that it combines the commonly used statistical parameters to provide an effective tool for bearing diagnostics, and is simple both conceptually and computationally. The method has been tested and the results show that it is an effective method for bearing diagnostics, particularly in providing a simple way for a human observer to visualize the diagnostics results on a 2-dimensional plane of the computer.

Acknowledgment

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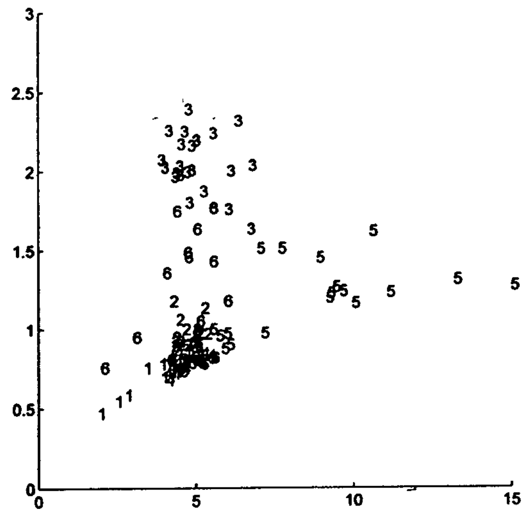

Figure 1 The feature space without intraclass transformation

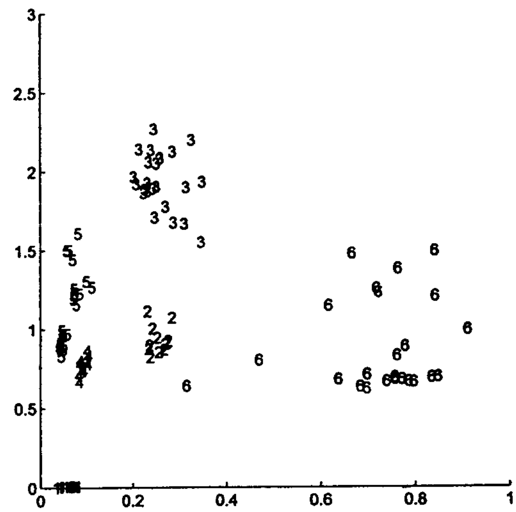

Figure 2 The feature space with intraclass transformation

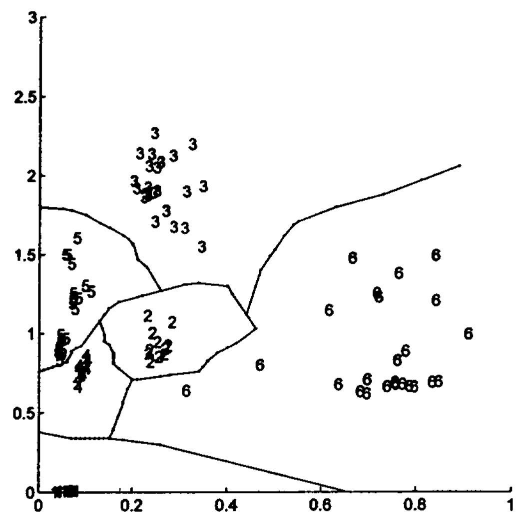

Figure 3 The classification space

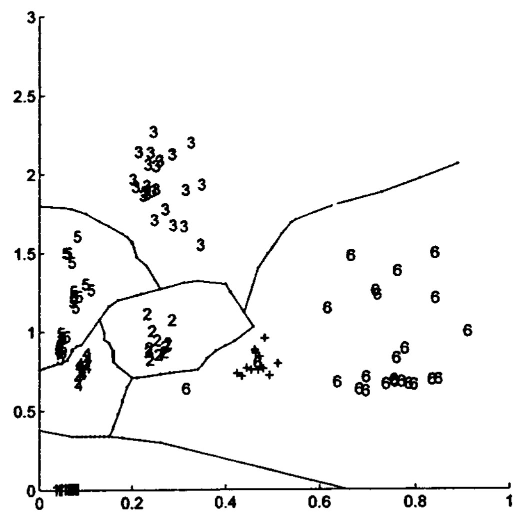

Figure 4 The result of bearing diagnostics